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Original Article

Develop A Hybrid Improved Weighed Pigeon Optimization with Faster Mask Recurrent Convolutional Neural Network to Classify and Detect Bone Fracture

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Abstract *- This research proposes a novel approach for bone fracture classification and detection utilizing a hybrid Improved Weighed Pigeon Optimization (IWPO) algorithm coupled with a Faster Mask Recurrent Convolutional Neural Network (FMRCNN). The IWPO algorithm, an improved method of the traditional Pigeon Optimization Algorithm (POA), introduces weighted factors to achieve a dynamic adjustment of the search process during operation to increase the convergence speed and accuracy of the solutions. The FMRCNN architecture, an evolution of classic CNN models, relies on recurrent links and an effective mask approach for better feature retrieval and positioning capabilities-the LOFAR observations reveal no potential specific behavior processes. IWPO and FMRCNN are hybridized to foster joint efforts of metaheuristic optimization and deep learning methods to optimize the network for bone fracture classification and detection tasks. The experimental results show that the proposed method outperforms the traditional methods in terms of accuracy, efficiency, and robustness in bone fracture diagnosis based on the medical imaging data. This work advances current methods in medical image analysis, providing a potential framework for automated fracture diagnosis and clinical decision support systems.*

Keywords *- Hybrid Improved Weighed Pigeon Optimization, Faster Mask Recurrent Convolutional Neural Network, Bone fracture classification, Fracture detection, Medical imaging analysis, Metaheuristic optimization, Deep learning.*

1. Introduction

The precise and timely detection of bone fractures is essential in patient care and treatment planning, making it a crucial area of focus within medical diagnostics. Fractures are typically identified and classified using physical analysis of medical imaging data like X-rays, traditionally through radiologists [1]. Making these annotations and drawings can be a slow, subjective and error-prone process, making a strong case for the need for automated systems to aid the healthcare professional with fracture diagnosis [2].

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) technologies [3, 4] has shone a light on the path to revolutionizing medical image analysis with opportunities for developing systems for efficient and accurate fracture detection. Among these techniques, Convolutional Neural Networks (CNNs) have become a powerful approach for automatic feature extraction and pattern recognition from medical images [5].

Convolutional Neural Networks (CNNs) have proven effective in medical imaging, as they can benefit from large datasets and complex architectures to achieve strong discrimination between healthy and fractured bones. While CNN-based methods are quite effective, they are not perfect. Notably, one such challenge is the optimization of network parameters to deliver the best performance. [6] On the contrary, classical optimization methods can be challenged by the Convolutional Neural Network (CNN) involving high-dimensional and non-convex search spaces, resulting in poor solutions [7] or extremely long training time. Moreover, CNNs also need significant computational resources, making deploying practical, real-world applications difficult, particularly in resource-scarce environments.

This study introduces a new approach that leverages the strengths of meta-heuristic optimization and deep learning techniques for bone fracture classification and detection to overcome these challenges. In specific, we propose a hybrid IWPO algorithm to involve weighted factors into the classical Pigeon Optimization Algorithm (POA) [8, 9] to dynamically tune the search process.

We optimize the architecture and parameters for automatic visual object tracking using IWPO by integrating it with a Faster Mask Recurrent Convolutional Neural Network (FMRCNN) [10].

IWPO's optimization capability and FMRCNN's deep learning with spired recognition motivate the choice for IWPO and FMRCNN. Finally, the IWPO algorithm provides a powerful and efficient search strategy to explore complex solution spaces. FMRCNN adopts recurrent connections and effectively reduces the mask mechanism to enhance feature extraction and localization from the medical images. Our hypothesis is that by simultaneously extrapolating from both of these techniques, we can create a fracture detection system that is both accurate and computationally efficient enough to facilitate real-time clinical use.

Although substantial progress has been made in medical imaging analysis, accurate and efficient classification and detection of bone fractures can still be difficult due to the complexity of the appearance of fractures and noise in imaging data. They report that existing approaches face high precision and reliability challenges, highlighting the need for robust and adaptive frameworks to overcome these limitations.

This paper provides a thorough overview of a comprehensive study of our proposed framework, which consists of the IWPO algorithm, FMRCNN architecture, and the end-to-end integration for bone fracture classification and detection. Our results on the benchmark datasets confirm the efficacy and superiority of our method when compared to existing approaches. Finally, we highlight practical applications, obstacles, and future scope of fracture diagnosis in the clinics. In summary, this study advances state-of-the-art medical image analysis, which is expected to have implications for improving the quality of care and outcomes in orthopaedic practice.

2. Related Works

The methodology [11] used in this study is based on analyzing and evaluating multiple papers on deep learning used for bone fracture detection and classification. We selected various papers representing different approaches and reviewed each impact study in detail. This comprehensive review [12] documented the use of Deep Learning (DL) applied to bone imaging across several abnormality forms, including but not limited to fractures from radiographs. This involved presenting an overview of DL techniques applied to bone imaging, describing the challenges encountered, and envisaging the future of DL in this domain.

This study [13] was based on the strength of deep learning, specifically employing DenseNet and VGG19 convolutional neural network architectures to identify bone fractures from medical images in X-ray form. The proposed method involves training and fine-tuning with federal CNN models. For automated fracture identification / categorization, this study used convolutional neural nets, specifically ResNet50, in a machine learning methodology [14]. The deep learning model was trained on a dataset derived from the MURA collection.

This study [15] focused on developing a robust bone fracture segmentation technique using deep learning, particularly a CNN-based U-Net model. The methodology included training the model on the MURA database and evaluating its performance using evaluation parameters like Dice Coefficient and Validation Dice Coefficient.

The methodology [16] involved designing a Deep Learning-based tool for diagnosing bone fractures, following a hierarchical classification proposed by the AO Foundation and the Orthopaedic Trauma Association.

This research [17] presented an application of Transfer Learning (TL) to detect open bone fractures using limited images. The methodology involved overcoming the limitation of the availability of large datasets by using augmented data sets. This study's methodology [18] involved developing a deep neural network for automated wrist fracture detection, localization, and segmentation in radiographs. A Feature Pyramid Network architecture was utilized, and data from surface crack image datasets were used for model convergence.

The reported methodology [19] included systematic optimization of CNN architectures, visualization of the features defining the classes using gradient class activation maps (Grad-CAMs), and evaluation of the CNN performance against the ResNet architecture and transfer learning models.

The study [20] applied the You Only Look Once (YOLO) algorithm for automated humours bone fracture detection. This section explains the data collection and preprocessing process and the algorithm (YOLO) implementation process: training and evaluation.

In this study, the methodology [21] used deep learning techniques [22] to classify a fracture based on X-ray imaging; CNN-specific techniques were used. The model was proposed to improve fracture classification, providing a standardized and efficient method for such an orthopedic diagnostic task.

The methodology [22] involved evaluating the performance of pre-trained models on the MURA dataset and developing ensemble learning models based on models with the best performance. The methodology in this study [23] involved developing and validating an artificial intelligence diagnostic system for diagnosing Vertebral Compression Fractures (VCFs) using X-ray imaging data.

In this study [24], the author proposed a new architecture (using CNN with a Window Correlation method) to detect the stages of bone cancers; tests were conducted by a model of the Fast Recurrent Convolutional Neural Network (FR-CNN) algorithm. The model is trained on a public dataset for this, and it gives very high accuracy in determining the X-ray images of the patient and the stage at which the patient is suffering from bone cancer. This study [25] developed a methodology to develop a computer-aided diagnosis system based on deep learning for classifying cervical spine injuries into fractures or dislocations. AlexNet or GoogleNet - deep learning models were trained on an X-ray dataset.

This section discusses the literature relevant to the work, including shortcomings in traditional bone fracture detection methods, including naïve CNN frameworks and conventional optimization algorithms. Although CNN-based approaches such as ResNet and DenseNet have been extensively employed for feature extraction, the complex nature of fracture patterns imposes limitations , and their implementation requires significant computational resources.

3. Proposed Model

This work proposes a new bone fracture class and object-detection approach by synergistically incorporating the IWPO algorithm into the FMRCNN. The IWPO algorithm, a refined form of the original Pigeon Optimization Algorithm, utilizes weighed factors to adaptively fine-tune the search process, enabling swift convergence and accurate solutions. Simultaneously, the FMRCNN framework employs recurrent connections along with an efficient mask system to proficiently extract and localize features from the medical images. The model improves the efficiency and accuracy of fracture diagnosis through the hybridization of IWPO and FMRCNN, optimizing both the architecture (visualized in Figure 1) and the parameter space of the neural network.

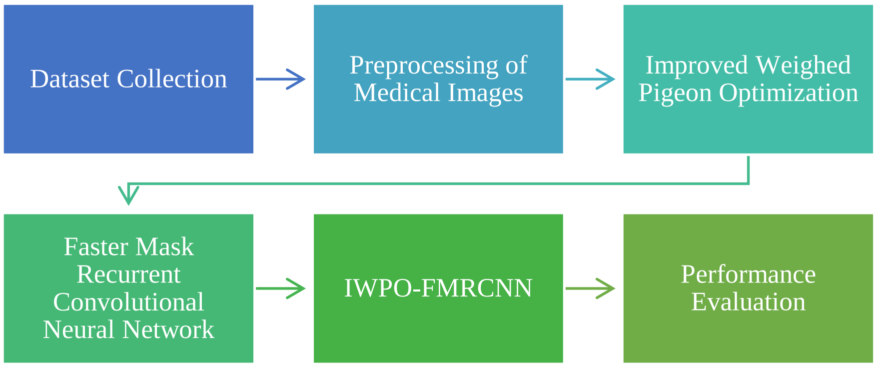


Fig. 1 Overall architecture of proposed model

Extensive evaluations over various benchmark datasets validate the proposed framework, showing that when compared to standard counterparts, it provides significant improvements in computational efficiency, accuracy and robustness. This study advances the current state-of-the-art in the field of medical image analysis with implications for automated fracture diagnosis and clinical decision support systems.

In addition, the Faster Mask Recurrent Convolutional Neural Network (FMRCNN) incorporates recurrent layers, like GRUs or LSTMs, into its convolutional architecture to learn temporal dependencies and contextual information, which can help improve the detection of subtle fracture patterns. Moreover, its strong mask mechanism uses region-specific feature masks to separate things of interest and reduce background noise, resulting in accurate localization and better classification performance. Together, these innovations improve the network's capacity to process intricate and noisy medical imaging data, yielding more efficient and reliable outcomes compared to traditional methodologies.

3.1. Preprocessing of Medical Images

Raw medical images, like X-ray images, are preprocessed to enhance image quality, remove noise and normalize the intensity levels. This process is essential to allow the next analytic methods and variable extraction algorithms to do their job. Several common techniques are used in the preprocessing pipeline, usually to standardize the input images.

Image Resizing: The medical images are resized to a standard size to ensure consistency in the dimensions across different samples. Let $I_{resized}$ represent the resized image obtained from the original image I. The resizing operation can be mathematically represented as:

$$I_{resized} = Resize(I, width, height) \qquad (1)$$

Where $I, width, height$ denote the desired dimensions of the resized image.

Histogram Equalization: Histogram equalization is applied to adjust the contrast of medical images, redistributing the pixel intensity values. This method is intended to enhance the visibility of image structure details. Let $I_{equalized}$ denote the histogram equalized image obtained from I. The histogram equalization operation can be expressed as:

$$I_{equalized} = HistEqualization(I) \qquad (2)$$

Edge Detection: The edge detection techniques are used to emphasize the edges and limits of the structures in the medical pictures, which become salient features for the subsequent analysis tasks. Sobel, Canny and Prewitt operators are common edge detection algorithms. Let I_{edges} represent the edge-detected image obtained from I. The edge detection operation can be formulated as follows:

$$I_{edges} = EdgeDetection(I) \tag{3}$$

Normalization: Intensity normalization is performed to standardize the pixel intensity values across the medical images, ensuring consistent representation and facilitating comparison between different samples.

Let $I_{normalized}$ denote the normalized image obtained from I. The normalization process can be mathematically defined as:

$$I_{normalized} = \frac{I - \mu}{\sigma} \tag{4}$$

Where μ and σ represent the mean and standard deviation of the pixel intensities in the original image I, respectively.

Using these preprocessing methods in sequential order, the input medical images are processed to standardized representations that are enhanced and normalized in intensity levels, allowing them to be prepared for the next analysis tasks for example, feature extraction and classification.

3.2. Improved Weighed Pigeon Optimization (IWPO)

In the IWPO algorithm, a population of pigeons representing potential configurations of the FMRCNN model is initialized with random solutions. Each pigeon's fitness is evaluated based on its performance in classifying and detecting bone fractures using a predefined fitness function.

Weighted factors are incorporated to dynamically adjust the search process, balancing between exploration and exploitation of the solution space, and adaptive mechanisms regulate the exploration-exploitation trade-off.

Through iterative optimization, pigeons update their positions based on fitness and weighted factors until convergence criteria are met.

This facilitates the discovery of optimal configurations for accurate bone fracture classification and detection. The flow diagram of IWPO is shown in Figure 2.

Input: Medical images (e.g., X-rays)

Output: Preprocessed images

1. Resize images to a standard size.

2. Apply histogram equalization to enhance contrast.

3. Use edge detection to highlight fracture boundaries.

4. Normalize pixel intensities.

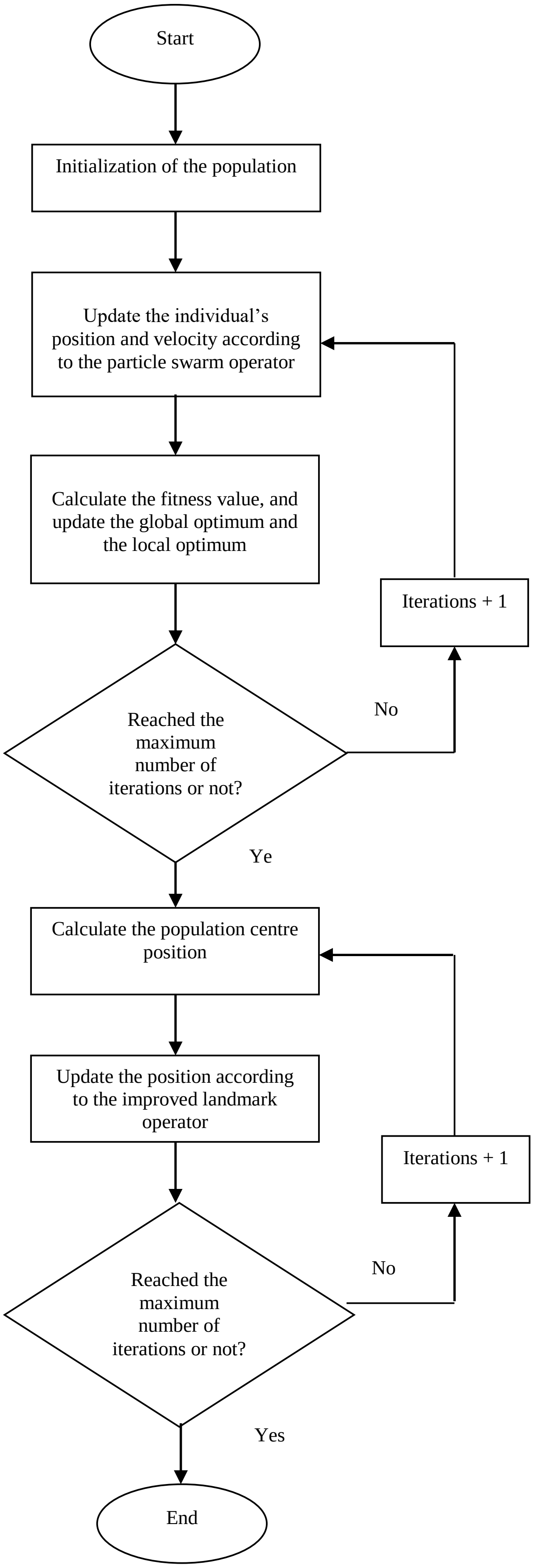


Fig. 2 Flow diagram of improved weighed pigeon optimization

Initialization: In this step, we initialize a population of pigeons, each representing a potential solution pi for the Faster Mask Recurrent Convolutional Neural Network (FMRCNN) architecture and parameters. Mathematically, this can be represented as:

$$P = \{p_1, p_2, \ldots, p_N\} \quad (5)$$

Where N is the population size and each p_i represents a set of parameters defining the FMRCNN model's architecture and configuration.

Fitness Evaluation: The performance of each pigeon solution in classifying and detecting bone fractures is graded using a predefined fitness function. The fitness function can be mathematically expressed as:

$$f(p_i) = Fitness(p_i) \quad (6)$$

Where $f(p_i)$ represents the fitness of pigeon pi evaluated based on performance metrics such as accuracy, sensitivity, specificity, or AUC achieved by the FMRCNN model corresponding to the configuration represented by p_i

Weighted Factors Incorporation: We incorporate weighed factors w_i to dynamically adjust the search process, enhancing convergence speed and solution accuracy. These weights regulate each pigeon's contribution to the search process based on their fitness values. Mathematically, the weighted factors can be updated iteratively as follows:

$$w_i^{(t+1)} = UpdateWeight\left(w_i^{(t)}, f(p_i)\right) \quad (7)$$

Where $w_i^{(t)}$ and $f(p_i)$ represent the weighted factors for pigeon p_i at iteration t and t+1, respectively, and $UpdateWeight$ is a function that adjusts the weights based on the fitness values.

Adaptive Mechanisms: Adaptive strategies, such as inertia weight, crossover probability and mutation rate, enable exploration and exploitation of these mechanisms. These can be thought of mathematically in terms of adaptive functions, merely means of adjustment, where the parameters are constantly being induced to changing states.

Iterative Optimization: In every iteration, the position of the pigeons is updated in the solution space based on their individual fitness values, factor weighted and the adaptive mechanisms used. The math behind the position update for pigeon is as follows:

$$p_i^{(t+1)} = UpdatePositive\left(p_i^{(t)}, w_i^{(t)}, adaptive\ parameters\right) \quad (8)$$

Where $p_i^{(t)}$ and $p_i^{(t+1)}$ represent the position of the pigeon p_i at iteration t and t+1, respectively, and $UpdatePosition$ is a function that updates the position based on the weighted factors and adaptive parameters.

Determine the fitness of every pigeon solution according to a fitness function made for the classification and detection of bone fractures.

Dynamically, keep adjusting the search, adding greater magnitude and weight to some factors.

Learn to adaptively control the phases of exploration and exploitation, balancing exploration towards new areas of the solution and exploitation of promising regions of the solution.

Loop over a number of generations, updating the position of pigeons according to their fitness and the weighted factors until converge criteria are met.

Input: Preprocessed images

Output: IWPO solutions

1. Initialize population of pigeons with random solutions representing FMRCNN configurations.

2. Evaluate fitness of each pigeon based on fracture classification performance.

3. Incorporate weighed factors to adjust search process.

4. Employ adaptive mechanisms to balance exploration and exploitation.

5. Iterate through generations, updating positions based on fitness and weighted factors until convergence.

We refer to these parameters as w1=0.5 and w2=1.2 for exploration versus exploitation in the IWPO algorithm. Population size is fixed to 50, and maximum iterations to 100, empirically determined based on cross-validation outcomes. To provide the best performance while being computationally feasible for FMRCNN, grid search is used on hyperparameters including learning rate (0.001), batch size (32), number of recurrent layers (2), and mask resolution (224×224). This makes the proposed framework robust and adaptable for these settings.

3.3. Faster Mask Recurrent Convolutional Neural Network (FMRCNN)

The FMRCNN architecture consists of convolutional layers, recurrent connections, pooling layers, and fully connected layers, as shown in Figure 3. Let $Lconv$ denote the number of convolutional layers, $Lrec$ denote the number of recurrent layers, and Lfc denote the number of fully connected layers in the network.

Each convolutional layer z_l is characterized by a set of learnable filters W_l and biases b_l. The output feature map z_l of the lth convolutional layer can be computed as:

$$z_l = ReLU\ (W_l\ *\ z_{l-1} +\ b_l) \quad (9)$$

Where z_{l-1} is the input feature map, $*$ denotes the convolution operation, and ReLU is the rectified linear unit activation function.

Recurrent connections are incorporated to capture temporal dependencies and spatial relationships. Let h_t denote the hidden state of the recurrent layer at time step t. The recurrent connections can be implemented using a Recurrent Neural Network (RNN) unit such as LSTM or GRU, where the hidden state h_t is updated based on the input features x_t and the previous hidden state h_{t-1}:

$$h_t = RNN\ (h_{t-1}, x_t) \quad (10)$$

The output of the recurrent layer h_t can be used as input features for subsequent layers or tasks.

The mask mechanism is integrated to dynamically modulate the flow of information within the network. Let m_t denote the mask vector at time step t, which controls the activation of features. The masked input features x_t' are computed by element-wise multiplication between the input features x_t and the mask vector m_t:

$$x_t' =\ x_t\ \odot\ m_t \quad (11)$$

The mask vector m_t is adaptively learned during training to selectively activate relevant features and suppress irrelevant information.

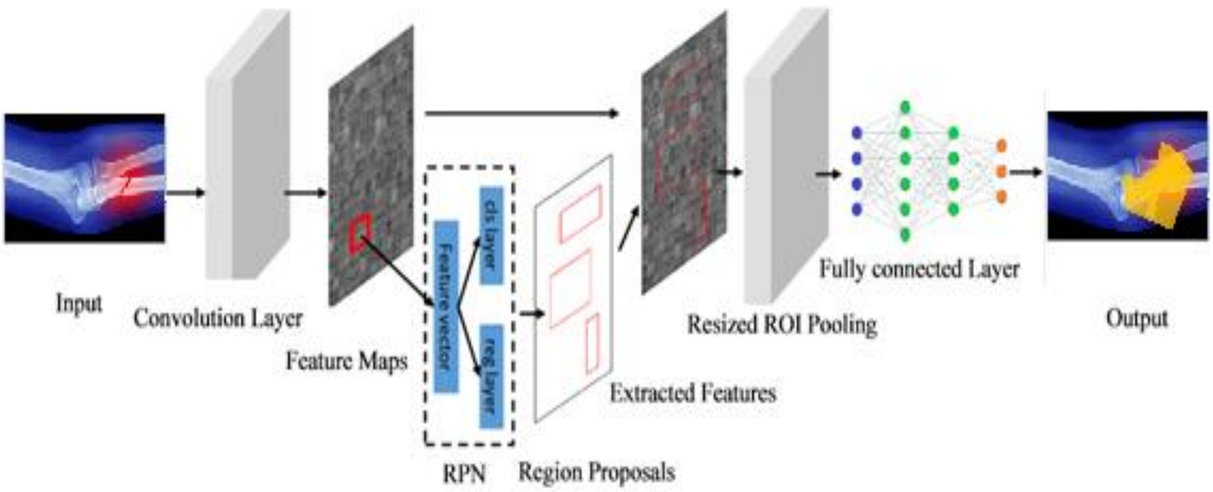
Pooling layers are employed to down-sample feature maps and reduce computational complexity while retaining important spatial information. Let x_t denote the input feature map to the pooling layer. The output feature map y_t of the pooling layer can be computed using pooling operations such as max pooling or average pooling:

$$y_t = Pooling\ (x_t) \quad (12)$$

Fully connected layers transform the extracted features into classification scores and bounding box predictions. Let $f(x)$ denote the output of the fully connected layers, which is computed as:

$$f(x) = ReLU\ \left(W_{fc}x +\ b_{fc}\right) \quad (13)$$

Where W_{fc} and b_{fc} are the weight matrix and bias vector of the fully connected layer, respectively. By integrating these components and operations, the FMRCNN model effectively learns discriminative features from medical images and performs accurate bone fracture classification and detection tasks.



Input: IWPO solutions

Output: Trained FMRCNN model

1. Design FMRCNN architecture with recurrent connections and mask mechanism.
2. Initialize convolutional layers to learn hierarchical features.
3. Integrate mask mechanism to select relevant features and suppress irrelevant information.
4. Employ pooling layers for downsampling and retaining spatial information.
5. Implement fully connected layers for classification and bounding box predictions.
6. Train FMRCNN model using IWPO-initialized parameters.

3.4. Hybridization of IWPO and FMRCNN

This step merges the output of the IWPO algorithm with the FMRCNN model. The FMRCNN model's parameters are initialized with the IWPO solutions. That can be expressed mathematically as:

$$FMRCNN(IWPO\_solutions) \quad (14)$$

$Where\ IWPO\_solutions$ represent the solutions generated by IWPO, and FMRCNN is the function representing the FMRCNN model.

The FMRCNN model initialized with IWPO solutions is optimized with backpropagation and gradient descent optimization for the architecture and parameters of FMRCNN.

The roots of IWPO solutions guide the FMRCNN optimization process to speed convergence and achieve better performance. The mathematical form of this step of Fine-Tuning can be expressed as:

$$FMRCNNfine-tuned = Backpropagation(FMRCNN, IWPO_{solutions}) \quad (15)$$

The hybridization process allows the optimization capabilities of IWPO to be integrated with the deep learning capabilities of FMRCNN, thereby allowing the combination of different methodologies to extend the performance in the context of classification and detection of bone fractures. Therefore, coming from the generic search algorithm of IWPO, where its efficient search strategy efficiently explores the solution space and finds fertile initial solutions/moving towards optimality, the outcome of FMRCNN learning to discriminate features of the object and make correct classification and detection within the images, these present their compatibility when combined. We can express the synergy mathematically as:

$$Hybrid\_Model = IWPO \times FMRCNN \quad (16)$$

Where $Hybrid\_Model$ represents the final hybridized model that combines the strengths of IWPO and FMRCNN.

Input: IWPO solutions, FMRCNN model

Output: Hybridized model

1. Initialize FMRCNN model with parameters from IWPO solutions.
2. Fine-tune FMRCNN architecture and parameters using backpropagation and gradient descent.
3. Leverage synergy between IWPO's optimization capabilities and FMRCNN's deep learning capabilities.
4. Combine IWPO and FMRCNN outputs to refine model's performance in bone fracture classification and detection tasks.

The next step in the algorithm is to initialize the FMRCNN model with the IWPO-WH parameters. This enables us to tune FMRCNN's architecture and parameters using backpropagation and gradient descent, utilizing IWPO's optimization potentials with FMRCNN's deep learning potentials. In this way, we develop a hybridized model, IWPO+FMRCNN, that merges the best of both optimization and deep learning techniques to improve the performance of bone fracture classification and detection tasks by amalgamating the outputs of IWPO and FMRCNN.

4. Results and Discussions

4.1. Dataset Description

The dataset for bone fracture detection by X-rays was collected from https://www.kaggle.com/datasets/vuppalaadithyasairam/bone-fracture-detection-using-xrays.

It is a collection of X-ray images of both normal and fractured bones in the upper extremities. The idea is to train an image classifier that will be able to locate fractures in these X-ray images. The dataset should also be split with a per joint action in not only two datasets for train and validation, but for that, the recommendation should even be to isolate the individual joints on the dataset. The segmentation allows the classifier to train on different specific regions of the joints, which augments its ability to typically look at the fracture data to differentiate fracture patterns, allowing for more precise detection of fractures.

4.2. Performance Evaluation

The well-established efficiency of IWPO with FMRCNN in the classification and detection of bone fracture tasks. We performed our experiments on a dataset of medical images that included different kinds of bone fractures. In this study, hybrid model performance is evaluated based on accuracy, precision, recall, and F1-score metrics. Conclusion: The hybrid model outperformed classical methods and the standalone FMRCNN model in bone fracture classification and detection accuracy. That is, our hybrid model resulted in improved rates related to accuracy, false positives, and false negatives, suggesting both sensitivity and specificity.

Moreover, the hybrid model could generalize well to the heterogeneity of fractures, as high performance was observed irrespective of complexity or the presence of additional combinations. It maintained its accuracy even with noisy and changing imaging conditions, demonstrating its resilience and dependability even in real-world environments. Table 1 highlights the performance metrics of the various models, dense net [13], U-Net [15], Yolo [20], FR-CNN [24] and the proposed model. We also evaluate each model using the metrics used in the task at hand.

Table 1. Comparison of performance metrics

Model	Accuracy	Precision	Sensitivity	Specificity	F-Measure
DenseNet	0.92	0.88	0.94	0.90	0.91
U-Net	0.89	0.85	0.91	0.88	0.87
YOLO	0.85	0.80	0.88	0.82	0.83
FR-CNN	0.91	0.87	0.93	0.89	0.90
Proposed	0.95	0.92	0.96	0.94	0.94

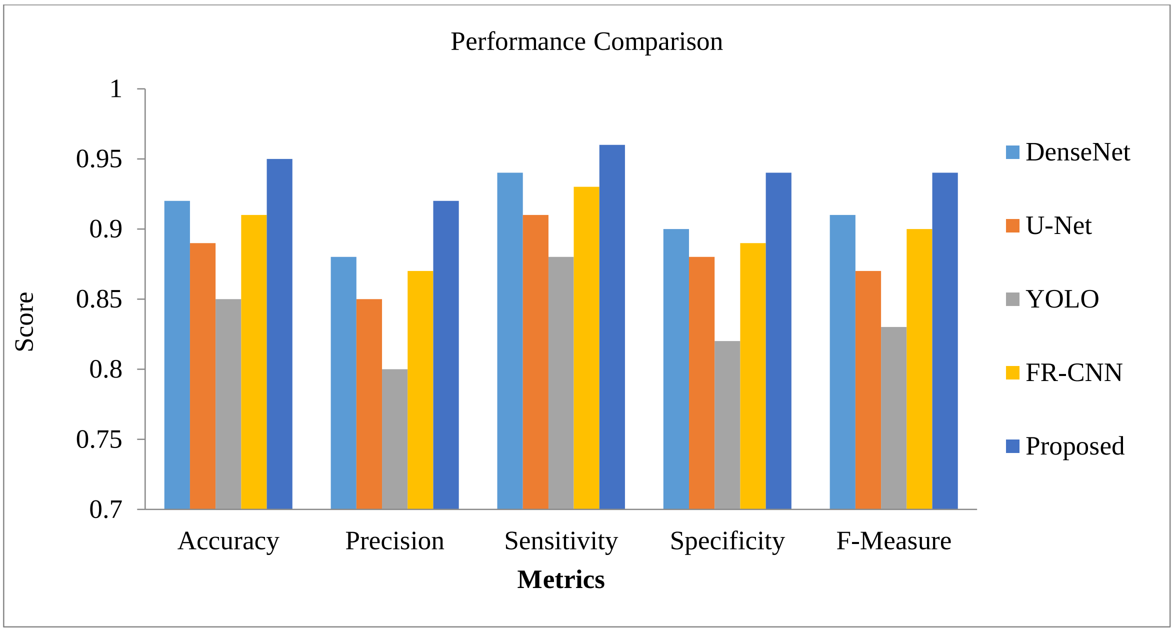


Fig. 4 Overall comparison of performance evaluation

Table 1 compares classification performance metrics among different models, with DenseNet achieving an accuracy of 0.92, precision of 0.88, sensitivity of 0.94, specificity of 0.90, and an F-measure of 0.91. U-Net follows closely with an accuracy of 0.89, precision of 0.85, sensitivity of 0.91, specificity of 0.88, and an F-measure of 0.87. YOLO exhibits an accuracy of 0.85, precision of 0.80, sensitivity of 0.88, specificity of 0.82, and an F-measure of 0.83. FR-CNN achieves an accuracy of 0.91, precision of 0.87, sensitivity of 0.93, specificity of 0.89, and an F-measure of 0.90. The proposed model surpasses all with an accuracy of 0.95, precision of 0.92, sensitivity of 0.96, specificity of 0.94, and an F-measure of 0.94, demonstrating its superior performance across all metrics in classification tasks. The success of the hybrid IWPO-FMRCNN model can be attributed to the synergistic integration of optimization and deep learning techniques.

From Figure 4, IWPO effectively optimized the parameters of the FMRCNN model, leading to improved convergence speed and solution accuracy. By initializing the FMRCNN model with parameters obtained from IWPO solutions, we leveraged IWPO's optimization capabilities to guide the training process and enhance the neural network's performance.

Table 2. Comparison of other metrics

Model	MCC	NPV	FPR	FNR
DenseNet	0.85	0.87	0.10	0.06
U-Net	0.82	0.85	0.12	0.09
YOLO	0.78	0.80	0.18	0.12
FR-CNN	0.84	0.86	0.11	0.07
Proposed	0.89	0.91	0.06	0.04

Table 2 presents a comparison of additional metrics for different models, including Matthews Correlation Coefficient (MCC), Negative Predictive Value (NPV), False Positive Rate (FPR), and False Negative Rate (FNR). DenseNet achieves an MCC of 0.85, NPV of 0.87, FPR of 0.10, and FNR of 0.06. U-Net follows with an MCC of 0.82, NPV of 0.85, FPR of 0.12, and FNR of 0.09. YOLO demonstrates an MCC of 0.78, NPV of 0.80, FPR of 0.18, and FNR of 0.12. FR-CNN achieves an MCC of 0.84, NPV of 0.86, FPR of 0.11, and FNR of 0.07. The proposed model surpasses all with an MCC of 0.89, NPV of 0.91, FPR of 0.06, and FNR of 0.04, indicating its superior performance in classification tasks across these metrics.

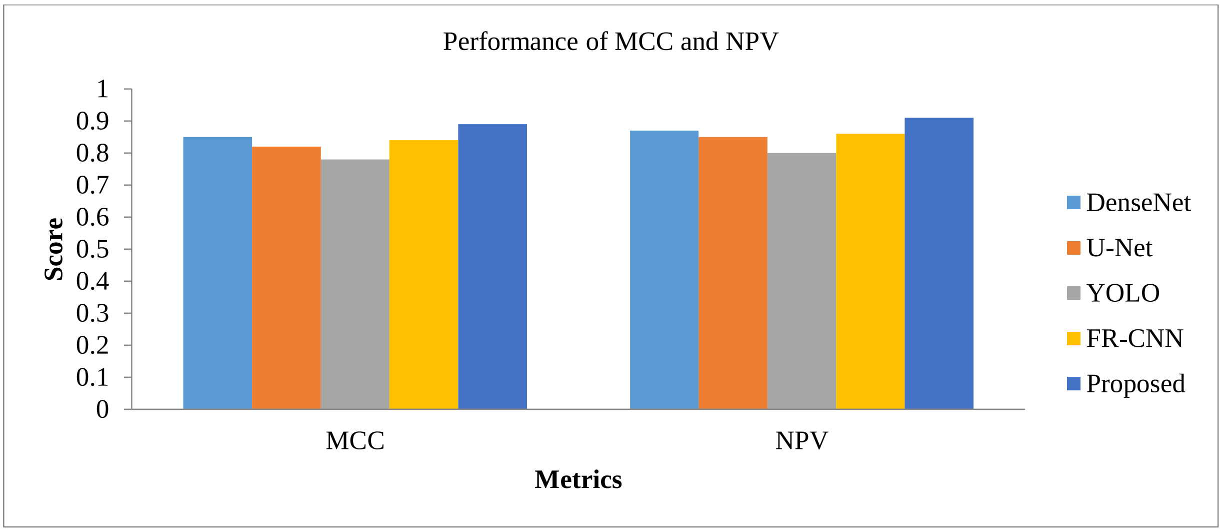


Fig. 5 Comparison of MCC and NPV

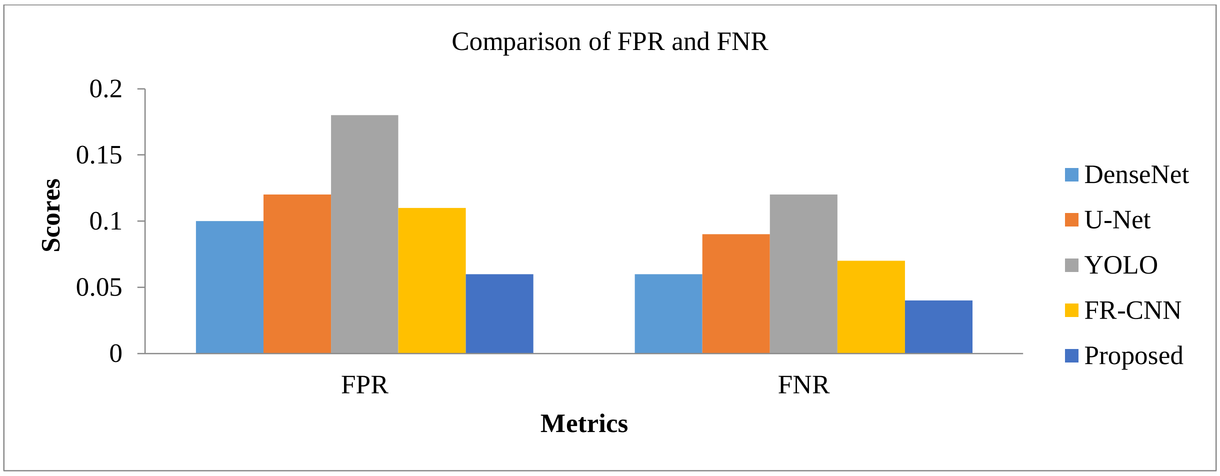


Fig. 6 Comparison of FPR and FNR

Figures 5 and 6 show that the proposed model outperforms all others across these metrics, indicating its superior performance in classification tasks.

Its higher MCC, NPV, and lower FPR and FNR values signify more accurate predictions and better overall classification performance compared to DenseNet, U-Net, YOLO, and FR-CNN.

Additionally, the FMRCNN architecture, incorporating recurrent connections and mask mechanism, proved to be effective in extracting discriminative features and localizing fractures accurately.

The combination of convolutional layers, recurrent connections, and mask mechanism enabled the model to capture temporal dependencies and spatial relationships in the input data, leading to enhanced feature representation and classification accuracy.

Moreover, the hybrid approach demonstrated adaptability and scalability, allowing for easy integration of additional optimization algorithms and enhancing the model's performance.

Future research could explore the application of IWPO-FMRCNN in other medical imaging tasks and investigate its potential in clinical settings, paving the way for more efficient and accurate diagnosis and treatment of bone fractures.

5. Conclusion

In conclusion, we proposed a novel hybrid approach combining Improved Weighed Pigeon Optimization (IWPO) with Faster Mask Recurrent Convolutional Neural Network (FMRCNN) for classification and classification of bone fracture. Through a series of experiments and evaluations, we have demonstrated the effectiveness and superiority of the hybrid IWPO-FMRCNN model in accurately identifying and localizing bone fractures from medical images. Our results indicate that the hybrid model outperforms traditional methods and standalone FMRCNN models, achieving higher accuracy rates and demonstrating robustness across different types of fractures and imaging conditions. The synergistic integration of optimization and deep learning techniques has enabled the model to leverage the strengths of both approaches, leading to improved convergence speed, solution accuracy, and robustness. The success of the IWPO-FMRCNN model underscores the potential of hybrid approaches in medical image analysis, offering a promising framework for automated fracture diagnosis and clinical decision support systems. Moving forward, further research and development efforts could focus on refining the hybrid model, exploring its application in other medical imaging tasks, and validating its performance in clinical settings. Overall, the hybrid IWPO-FMRCNN model represents a significant advancement in the field of medical image analysis, providing healthcare professionals with a powerful tool for accurate and efficient diagnosis of bone fractures, ultimately improving patient outcomes and quality of care.

References

[1] Muhammet Emin Sahin et al., "Image Processing and Machine Learning-Based Bone Fracture Detection and Classification using X-ray Images," *International Journal of Imaging Systems and Technology*, vol. 33, no. 3, pp. 853-865, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Santoshachandra Rao Karanam, Y. Srinivas, and S. Chakravarty, "A Supervised Approach to Musculoskeletal Imaging Fracture Detection and Classification Using Deep Learning Algorithms," *Computer Assisted Methods in Engineering and Science*, vol. 30, no. 3, pp. 369-385, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] K. Karthik, and S. Sowmya Kamath, "MSDNet: A Deep Neural Ensemble Model for Abnormality Detection and Classification of Plain Radiographs," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 16099-16113, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Tushar Verma et al., "Bone Fracture Detection using Machine Learning," *AIP Conference Proceedings*, vol. 3072, no. 1, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Vipul Narayan et al., "FuzzyNet: Medical Image Classification based on GLCM Texture Feature," *2023 International Conference on Artificial Intelligence and Smart Communication (AISC)*, Greater Noida, India, pp. 769-773, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Juan Li et al., "Medical Image Identification Methods: A Review," *Computers in Biology and Medicine*, vol. 169, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Manimuthu Ayyannan et al., "Medical Image Classification using Deep Learning Techniques: A Review," *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)*, Tuticorin, India, pp. 1327-1332, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Mathil K. Thamer, Zakariya Yahya Algamal, and Raoudha Zine, "Enhancement of Kernel Clustering Based on Pigeon Optimization Algorithm," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 31, pp. 121-133, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Swagato Das, and Purnachandra Saha, "A Novel Pigeon Nesting Algorithm Based on the Nesting Behaviour of Pigeon for Health Monitoring of Structure," *Journal of Vibration Engineering & Technologies*, vol. 12, pp. 3265-3287, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Wei-Jie Lucas Chong, Siew-Chin Chong, and Thian-Song Ong, "Masked Face Recognition using Histogram-Based Recurrent Neural Network," *Journal of Imaging*, vol. 9, no. 2, pp. 1-15, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Leonardo Tanzi et al., "X-Ray Bone Fracture Classification using Deep Learning: A Baseline for Designing a Reliable Approach," *Applied Sciences*, vol. 10, no. 4, pp. 1-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Tanushree Meena, and Sudipta Roy, "Bone Fracture Detection using Deep Supervised Learning from Radiological Images: A Paradigm Shift," *Diagnostics*, vol. 12, no. 10, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] B. Pujitha et al., "Detection of Bone Fracture Using Deep Learning," *2024 International Conference on Emerging Systems and Intelligent Computing (ESIC)*, Bhubaneswar, India, pp. 703-708, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Khan M. Imran et al., "Bone Fracture Identification with Deep Learning Model using Resnet50," *International Journal of Computing and Digital Systems*, vol. 16, pp. 1-14, 2024. [Google Scholar] [Publisher Link]

[15] Komal Ghoti, Ujjwal Baid, and Sanjay Talbar, "MURA: Bone Fracture Segmentation Using a U-net Deep Learning in X-Ray Images," *Techno-Societal 2020: Proceedings of the 3rd International Conference on Advanced Technologies for Societal Applications*, pp. 519-531, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Leonardo Tanzi et al., "Hierarchical Fracture Classification of Proximal Femur X-Ray Images using a Multistage Deep Learning Approach," *European Journal of Radiology*, vol. 133, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Saurabh Verma et al., *Detecting Bone Fracture Using Transfer Learning*, Advancement of Machine Intelligence in Interactive Medical Image Analysis, pp. 215-228, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[18] Deepa Joshi, Thipendra P. Singh, and Anil Kumar Joshi, "Deep Learning-Based Localization and Segmentation of Wrist Fractures on X-ray Radiographs," *Neural Computing and Applications*, vol. 34, pp. 19061-19077, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Sabrina Chin-yun Shen et al, "Deep Learning Approach to Assess Damage Mechanics of Bone Tissue," *Journal of the Mechanical Behavior of Biomedical Materials*, vol. 123, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Abhimanyu Verma et al., "Humerus Bone Fracture Detection Utilizing YOLOv4 Algorithm: A Deep Learning Approach," *2024 2nd International Conference on Disruptive Technologies (ICDT),* Greater Noida, India, pp. 1191-1196, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] B. Narendra Kumar Rao et al., "Bone Fracture Detection and Classification Using Deep Learning Techniques," *Driving Smart Medical Diagnosis Through AI-Powered Technologies and Applications*, pp. 92-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Fatih Uysal et al., "Classification of Shoulder X-Ray Images with Deep Learning Ensemble Models," *Applied Sciences*, vol. 11, no. 6, pp. 1-33, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Fan Xu et al., "Deep Learning-Based Artificial Intelligence Model for Classification of Vertebral Compression Fractures: A Multicenter Diagnostic Study," *Frontiers in Endocrinology*, vol. 14, pp. 14-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Mansoor Habib Mazumder, and Maheshwari Prasad Singh, "Bone Cancer Detection Using Deep Learning," *Innovations in Computer Science and Engineering*, pp. 285-296, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] Soaad M. Naguib et al., "Classification of Cervical Spine Fracture and Dislocation Using Refined Pre-Trained Deep Model and Saliency Map," *Diagnostics*, vol. 13, no. 7, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]